An Automated Shrimp Feeding System Using Passive Acoustic Monitoring and Faster R-CNN

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***Abstract*—Shrimp aquaculture plays a vital role in global seafood production, contributing substantially to food security, economic growth, and export revenue. Feed typically accounts for 40–60% of total production costs, making efficient feed management crucial for improving farm profitability and the sustainability of culture operations. Acoustic-based feeding strategies offer a promising solution by enabling demand-driven feed control through the detection of shrimp feeding sounds. However, reliable recognition in commercial ponds remains difficult due to strong background noise from aerators, pumps, diffusers, and rainfall, which overlaps with the frequency band of the feeding signals. In addition, the dependence on specialized software and high-performance computing resources hinders large-scale adoption. This study proposes a novel shrimp feeding sound recognition approach that converts acoustic signals into spectrogram images and employs a Faster R-CNN–based framework to regulate feed delivery in real time according to shrimp demand. A wavelet-based filtering method is introduced to effectively suppress ambient noise under practical farming conditions. Moreover, the developed open-source Python-based software enhances the feasibility of deploying intelligent acoustic-based feeding systems in commercial shrimp aquaculture. Experimental results demonstrate that the proposed system improves feed utilization efficiency and growth performance compared with traditional feeding practices.**

Keywords*—*Automated feeding system; faster R-CNN; passive acoustic monitoring; shrimp culture; whiteleg shrimp

I. Introduction

Shrimp aquaculture represents an important component of global seafood production, contributing significantly to food security, economic development, and export revenue in many countries. According to recent industry forecasts, the value of the global shrimp market may reach approximately $88 billion by 2030, expanding at an annual rate of around 6.5% [1]. As demand for aquatic products continues to rise and sustainability constraints become more stringent, the integration of advanced technologies into shrimp farming operations has emerged as a necessary direction for improving productivity and resource efficiency.

In shrimp farming, feed costs account for 40–60% of the total production expenses. Therefore, effective feed management is one of the most important factors in improving profitability and the sustainability of the culture system [2]. Underfeeding may result in poor growth and uneven size distribution, whereas overfeeding can deteriorate pond water quality, increase the risk of disease, and reduce production efficiency [2],[3]. In intensive shrimp farming, feeding operations are primarily based on three approaches: 1) manual feeding following the standard feeding practice (SFP), 2) the use of timer-based automatic shrimp feeders, and 3) demand feeding based on acoustic feedback generated by shrimp during feeding [2]. Under the manual feeding method, farmers broadcast feed directly onto the pond surface. This approach is low in cost, easy to implement, and flexible based on visual observation; however, it strongly depends on operator experience, is difficult to quantify accurately, may lead to overfeeding or underfeeding, and requires considerable labor [4],[5]. Timer-based automatic feeders have emerged as an alternative solution to overcome the limitations of traditional manual feeding, especially in medium- and large-scale farms where feed can be dispensed according to preprogrammed schedules [6-8]. Compared with manual feeding, such systems improve feeding efficiency, reduce feed waste, and lower labor costs [9],[10]. Although timer-based feeders operate according to fixed feeding schedules, they may still result in overfeeding or underfeeding and the accumulation of uneaten feed [11],[12]. The acoustic-based feeding method, also referred to as passive acoustic monitoring (PAM), enables more precise feeding control through the analysis of shrimp feeding sounds, thereby minimizing feed waste and helping maintain pond water quality [13-16]. This advanced feeding approach has been demonstrated to outperform manual and timer-based feeding approaches in terms of feeding efficiency and production performance [17].

In PAM-based shrimp feeding frameworks, accurate recognition of "click" sounds generated by shrimp during feeding is essential for automated feeder operation. However, a major challenge in detecting shrimp feeding sounds arises from background noise generated by aerators, pumps, air diffusers, and rainfall. These interferences overlap with the frequency band of the feeding "click" signals, degrade the signal-to-noise ratio, and consequently impair accurate detection and classification. In addition, the dependence on specialized software and high-performance computing platforms for real-time signal analysis continues to constrain the broader deployment of this advanced feed management technology in shrimp farming.

This study presents the design and implementation of a PAM-based automated feeding system for whiteleg shrimp (Litopenaeus vannamei) using deep learning. We propose a novel approach for recognizing whiteleg shrimp feeding sounds by converting acoustic signals into spectrogram images and employing Faster R-CNN (Faster Region-based Convolutional Neural Network) for automatic feature

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extraction and classification. Wavelet-based filtering is applied to effectively suppress background noise in acoustic signals collected from commercial shrimp ponds. The Short-Time Fourier Transform (STFT) was subsequently employed to convert the processed signals into spectrograms, which were then used to train the Faster R-CNN model. A fuzzy logic–based control algorithm was also developed to regulate the operation of the shrimp feed dispenser in accordance with the feeding demand of the shrimp. Experimental results show that the proposed automated feeding system improves feed utilization efficiency and growth performance compared with the traditional feeding method.

The main contributions of this study are summarized as follows:

- Introduces a novel method for recognizing shrimp feeding sounds using Faster R-CNN.
- Employs a wavelet-based denoising technique to effectively suppress background noise in real-world pond environments.
- Develops open-source Python-based tools for efficient processing and reliable recognition of shrimp feeding activity.
- Experimentally validates the performance of the proposed automated feeding system under real farming conditions.

The remainder of this study is organized as follows: Section II reviews related works on shrimp feeding sound recognition techniques for feeding automation. Section III describes the proposed method, including the system architecture, shrimp feeding sound acquisition and processing, the development of the Faster R-CNN–based recognition model, and the fuzzy logic–based feeder motor control algorithm. Section IV presents the experimental setup and results, including a comparison with the standard shrimp farming method. Section V concludes the study and discusses the limitations and directions for future work.

II. Related Works

In recent years, various techniques have been introduced to identify shrimp feeding "click" sounds, aiming to optimize feeding practices and advance automated feeding technologies. Specifically, Daniel et al. [18] proposed a context-aware acoustic classification framework for monitoring prawn feeding. The method detects characteristic feeding "click" sounds and utilizes a Context-Aware Dynamic Bayesian Network (CADBN) to represent the signals, enabling the extraction of robust feeding signatures expressed as temporal patterns of acoustic activity linked to feeding behavior. The authors in [19] introduced a dual-threshold strategy for detecting shrimp feeding "click" sounds in acoustically noisy pond environments. The approach integrates time-domain criteria, including signal amplitude and duration, with a band-pass filter in the 2–10 kHz range. This combination suppresses background interference, reduces false alarms, and yields more dependable identification of feeding events, thereby improving the accuracy of feeding activity monitoring.

In [20], Mel-Frequency Cepstral Coefficients (MFCC) and Linear Prediction Cepstral Coefficients (LPCC) were derived from acoustic recordings of shrimp feeding under various behavioral states. These features were then fed into a one-versus-rest Support Vector Machine (SVM) classifier. Laboratory experiments showed that the selected descriptors effectively characterized behavior-dependent acoustic variations, achieving classification accuracies of up to 93%. Peixoto et al. [21] employed Raven Pro software (Cornell University, USA) to inspect oscillogram and spectrogram representations of acoustic files recorded under background-noise-free conditions. A band-limited energy detector was then applied to automatically detect "click" events within a frequency range of 10–80 kHz and a signal duration of 5–50 ms. The histogram analysis tool provided in Microsoft Excel (Microsoft Corporation, USA) was subsequently applied to determine the rate distribution of clicks per minute for each recording. Study [22] proposed using the Librosa library, a Python package for audio analysis, to automatically detect shrimp feeding sounds. Audio recordings acquired under laboratory conditions were segmented into short intervals, and spectral-flux onset strength was computed to form an energy envelope. Peaks in this envelope were identified as shrimp clicks, providing the time stamps of feeding events.

Although substantial progress has been made in the recognition of shrimp feeding sounds, a clear research gap still exists. Most previous studies collected acoustic data under controlled laboratory conditions, where the recordings were largely free from background noise generated by aerators, air bubble diffusers, and other equipment commonly found in commercial ponds. As a result, when these methods are deployed in real farming environments, where ambient noise severely contaminates the signals, their effectiveness and robustness become critical concerns. In addition, the reliance on dedicated software packages and high-performance computing infrastructure further limits the practicality of implementing continuous, in-situ monitoring of shrimp feeding activity. These constraints highlight the need for open-source acoustic processing tools capable of automatically and reliably detecting shrimp feeding sounds under real pond conditions, thereby enabling wider deployment of automated feeding systems.

III. Methodology

A. System Architecture

Fig. 1 presents the overall architecture of the proposed automated shrimp feeding system. The system hardware consists of four main components: a hydrophone, a Central controller, a Server, and a shrimp feeder. An H1a hydrophone [23] is installed in the pond, near the feeding tray, to capture the acoustic signals generated by shrimp during feeding. The shrimp feeding sounds are amplified by a PA-4 amplifier [24], transmitted to the Central controller, and subsequently sent to the Server via a Wi-Fi connection. At the Server, an artificial intelligence algorithm analyzes the acoustic signals to determine the shrimp's feeding status. Based on this analysis, control commands are sent back to the Central controller to regulate the Shrimp feeder and dispense an appropriate amount of feed. The Central controller is supplied by a solar-powered battery, allowing reliable outdoor operation without reliance on the power grid.

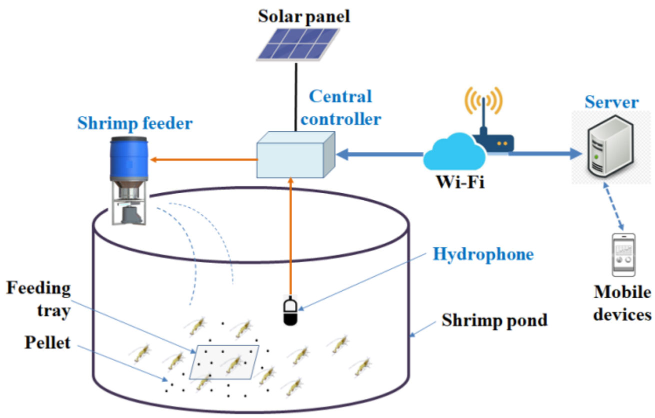


Fig. 1. Architecture of the proposed automated shrimp feeding system.

The Server acts as the main processing and decision-making unit of the system. It receives underwater acoustic data from the shrimp pond via a Wi-Fi connection and performs data storage, preprocessing, and deep learning–based signal analysis to evaluate shrimp feeding behavior. In this study, a Server equipped with an Intel Core i7-8550U processor running at 1.8 GHz and 8 GB of RAM was employed. A web interface was also developed to allow users to monitor the system operation by accessing the Server via mobile devices.

B. Characteristics of Shrimp Acoustic Signals

During feeding, the calcified mandibles of whiteleg shrimp collide and rub against each other, generating chewing sounds that are captured as "click" signals by the passive acoustic monitoring system. These signals are typically brief, exhibit higher frequency components than the background pond noise, occur intermittently, and increase in rate during active feeding periods [25].

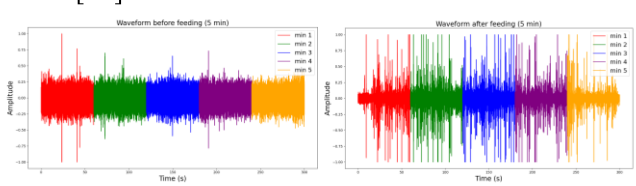


Fig. 2. Five-minute recorded signal waveform of shrimp sound: before feeding (left) and during feeding (right).

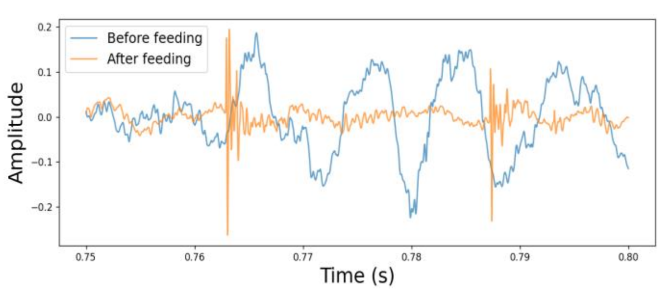


Fig. 3. "Click" sounds exhibit short duration and high-frequency components.

Fig. 2 shows the waveforms of five-minute shrimp sound recordings obtained before and during feeding. Before feeding, the chewing-related waveforms are sparsely distributed. In contrast, a much higher density of these waveforms is observed during feeding. Fig. 3 presents a 50-ms audio segment that highlights the "click" sounds produced during shrimp feeding. The clicks are short-duration transients with higher-frequency content compared with the low-frequency background noise, allowing them to be effectively separated through filtering techniques.

C. Acoustic Signal Acquisition and Processing

Fig. 4 presents the procedure for processing and extracting acoustic features from shrimp feeding sounds. Initially, acoustic signals in the shrimp pond are captured at a sampling rate of 44.1 kHz by the H1a hydrophone installed above the feeding tray on the pond bottom. The continuous recordings are subsequently divided into ten-second segments to enable efficient analysis and model training. Wavelet-based filtering is then employed to suppress noise in the signals. Next, the filtered audio is normalized to an amplitude range of [−1, 1] to maintain consistency among samples. Finally, spectrograms of shrimp feeding sounds are generated by applying the Short-Time Fourier Transform (STFT) [26] to the normalized signals.

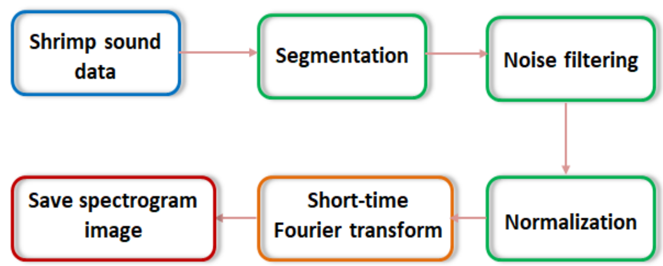
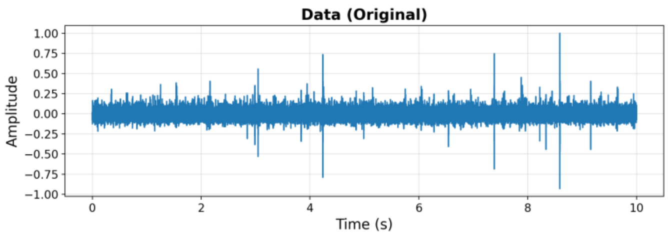


Fig. 4. Procedure for data preprocessing and acoustic feature extraction of "click" sounds.

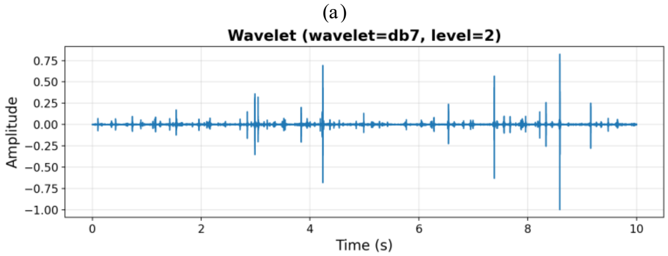
1) Noise filtering: In practical pond conditions, shrimp feeding sounds are masked by substantial background noise generated by aerators, air diffusers, and rainfall. According to previous studies [27] and the authors' field observations, the majority of the noise energy in shrimp farming environments is concentrated in the low-frequency range below 5 kHz. According to [28], feeding-related "click" sounds of whiteleg shrimp extend from 4 to 15 kHz, with most of their acoustic energy distributed under 10 kHz. Consequently, noise-reduction techniques must be applied to remove unwanted interference before analyzing the recorded signals.

The wavelet transform is widely recognized as an effective signal processing technique, particularly for denoising tasks [29]. Owing to its adaptability to nonstationary signals, it often provides superior performance compared with conventional filtering approaches [30],[31]. Shrimp chewing sounds exhibit time-varying amplitude and frequency characteristics that depend on feeding activity and typically persist for only a short duration. Consequently, wavelet-based filtering is well-suited for processing these acoustic events.

Selecting suitable filtering parameters is essential to retain the salient characteristics of the shrimp chewing signals while effectively suppressing noise. In this work, the filtering procedures were implemented using the open-source Python wavelet analysis library PyWavelets [32]. Based on empirical evaluation, a wavelet filter configured with wavelet = 'db7', threshold = 0.2, and level = 2 was found to be effective for processing shrimp feeding sounds in noisy real-world pond environments. Fig. 5 presents an example of the filtering results obtained for a representative audio segment. It can be observed that the background noise amplitude is significantly reduced, while the signal features become more prominent.



(a)



(b)

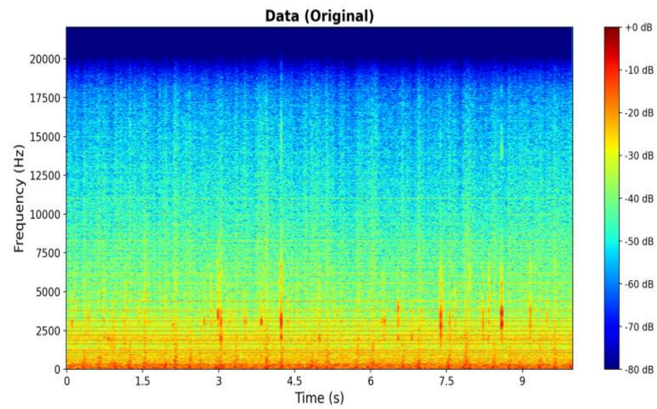
Fig. 5. Sound signal waveforms: (a) the original signal and (b) signal waveform after filtering and normalization.

2) Feature extraction: The filtered sound signals are processed using the STFT transform implemented in the SciPy library [33] to extract time-and frequency-domain features of shrimp feeding sounds. A parametric study conducted in this work demonstrates that an STFT configuration with a 1,024-sample window and 50% overlap provides effective performance. Furthermore, because shrimp feeding sounds are mainly distributed within the 3–8 kHz frequency band, the analysis is limited to this range to save computational resources and shorten model training time.

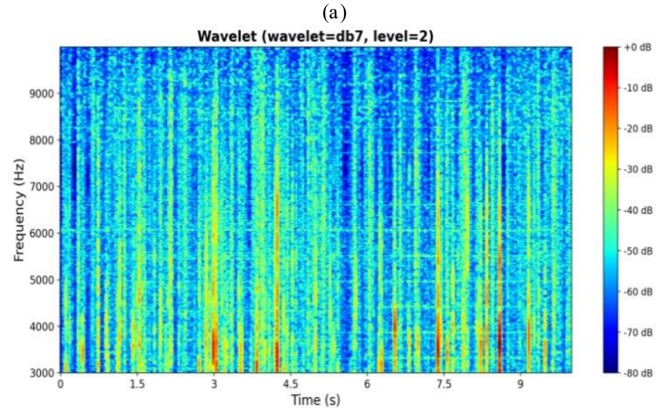
Fig. 6 presents the spectrogram of a sound segment acquired during shrimp feeding, showing both the original signal and the result after wavelet denoising. In the original signal (Fig. 6a), most of the spectral energy of the unfiltered acoustic data is concentrated within the 0–3 kHz band, likely originating from background noise generated by the aeration system and surrounding pond environment. After denoising (Fig. 6b), the low-frequency noise energy is significantly reduced, whereas the spectral components corresponding to the "click" pulses become more pronounced, predominantly within the 3–8 kHz band. The resulting spectrograms will serve as inputs to the deep learning model to automatically identify "click" events related to shrimp feeding activity.

D. Development of a Faster R-CNN–Based Detection Model

Faster R-CNN (Faster Region-based Convolutional Neural Network) is a widely adopted two-stage object detection framework well known for its superior localization and classification capability [34]. Although one-stage detectors such as YOLO [35] provide higher inference speed, two-stage approaches generally achieve superior accuracy for small and sparsely distributed objects. In spectrogram images of shrimp feeding sounds, the "click" events usually occupy small regions and are easily confused with background interference, making precise localization essential. A comparative study conducted by the authors shows that Faster R-CNN outperforms YOLO models (v9–v11, NAS, and World) in shrimp feeding spectrogram recognition. Therefore, Faster R-CNN was chosen in this study to maximize detection robustness and accuracy while still satisfying the near real-time processing requirements of the monitoring system.



(a)



(b)

Fig. 6. Spectrogram of an audio segment recorded during shrimp feeding: (a) original signal and (b) after wavelet-based denoising.

In this task, spectrogram images are used as the input for training the Faster R-CNN, where the "click" pulses are represented as the objects to be detected. The model integrates a convolutional feature extraction network (ResNet-50 backbone) with a Region Proposal Network (RPN) to generate candidate regions, followed by classification and bounding-box regression on the regions of interest, enabling precise localization of the "click" events in the spectrogram images. A total of 3,039 spectrogram images were generated from acoustic data collected from three ponds under real-world conditions, including noise from aerators, air diffusers, and environmental sources. The dataset spans multiple feeding cycles—pre-feeding, during, and post-feeding—to comprehensively capture shrimp feeding behavior and ensure generalizability. All images were resized to 640 x 640 pixels and partitioned into three subsets, namely training, validation, and testing, as summarized in Table I.

TABLE. I. DATASET FOR TRAINING, VALIDATION, AND TESTING

Type of Data	Number of Spectrogram Images
Training dataset	2,128
Validation dataset	608
Test dataset	303

Fig. 7 presents the loss curves of the training and validation sets of the Faster R-CNN model over 20 epochs. The training loss decreases rapidly during the initial epochs and gradually converges after approximately 10 epochs, while the validation loss remains low and relatively stable, with only minor fluctuations around the tenth epoch. The tenth epoch is identified as the optimal point at which the validation loss reaches its minimum value. The small gap between the training and validation losses indicates that the model learns effectively and generalizes well, with no evident overfitting due to the application of an early stopping strategy when further epochs no longer provide improvement.

Evaluation results on the independent test set show that the model achieves a Precision of 98.21%, a Recall of 100%, an mAP of 98.21%, and an F1-score of 99.09%, where the mAP is computed at an IoU threshold of 0.5. These metrics indicate that the model is capable of comprehensively detecting shrimp feeding "click" events (high recall) while maintaining high prediction precision, reflecting strong generalization performance on the test data.

Fig. 7. Training and validation loss curves.

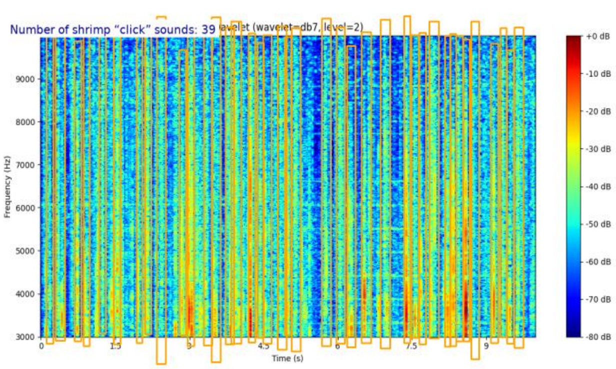


Fig. 8. Detection and counting results of "click" sounds using the faster R-CNN model.

Fig. 8 provides a visual illustration of the detection and counting results of the "click" pulses for a typical spectrogram image. It can be observed that the shrimp acoustic "click" pulses are detected and localized in the spectrogram image by the Faster R-CNN model. The predicted bounding boxes are primarily concentrated within the 3–8 kHz frequency band of the "click" signals, demonstrating the model's ability to accurately localize short-duration acoustic events even in noisy environments. This result demonstrates the feasibility of the spectrogram feature–based method for detecting "click" sounds.

E. Control Algorithm of the Shrimp Feeder

In the automated feeding method based on acoustic feedback, the feed supply is determined according to the intensity and occurrence frequency of the sounds produced by shrimp during feeding. In this study, a fuzzy logic algorithm was developed to establish the relationship between the operating time of the shrimp feeder motor and the density of shrimp "click" sounds [36],[37]. The input variable of the algorithm is the number of "click" sounds per minute, representing the intensity of shrimp feeding behavior. It is defined over the interval $[0, N]$ and is described by five linguistic fuzzy levels: Very Low, Low, Medium, High, and Very High (Fig. 9a). The value of N was determined based on the stocking density and was set to 60 clicks/minute in this experiment. The output variable corresponds to the operating time of the feeder motor (in seconds), bounded within the interval $[0, T]$, and is also represented by the linguistic fuzzy set: Stop, Short, Medium, Long, Very Long, and Maximum (Fig. 9b). The value of T was determined experimentally and was set to 6s in this study. Trapezoidal membership functions were employed for both the input and output variables to simplify the inference process and to meet the implementation requirements of the embedded system.

Fig. 10 illustrates the input–output characteristic of the fuzzy controller, showing the relationship between the density of "click" sounds and the shrimp feeder operating time. The characteristic curve consists of three main control regions: 1) the Stop region, where the input signal is below the threshold of 15 clicks/minute, resulting in a feeder activation time of zero; 2) the Increasing region, in which the feeding duration increases proportionally with shrimp feeding activity, ensuring a smooth load increment; and 3) the Saturation region, where the input exceeds 50 clicks/minute and the shrimp feeder operates at its maximum rate. The above threshold values were determined based on the stocking density (i.e., the average number of shrimp at the feeding tray) and empirical observations.

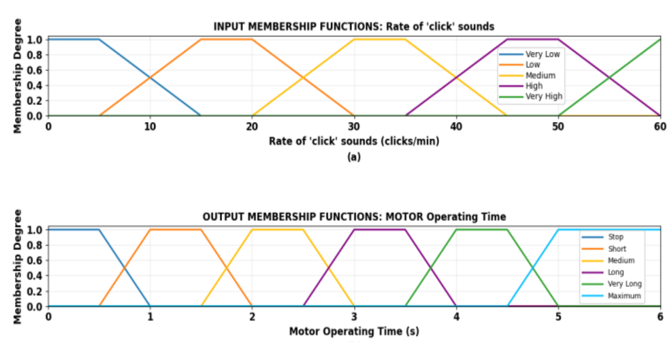


Fig. 9. Input (a) and output (b) membership functions of the fuzzy logic control algorithm.

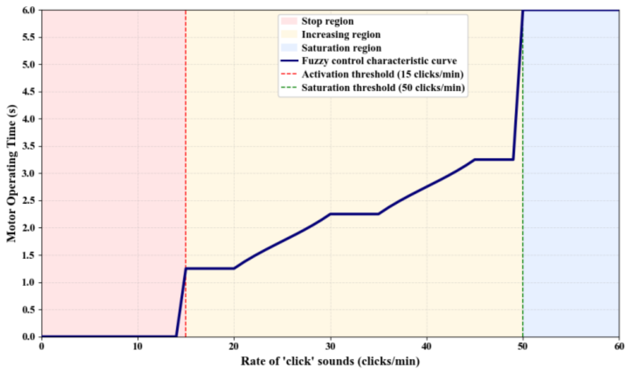


Fig. 10. The relationship between the number of detected "click" sounds and the operating time of the feeder motor.

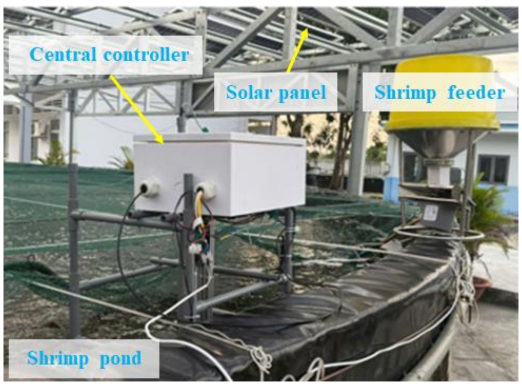


Fig. 11. The automated feeding system deployed at the shrimp pond.

IV. Experimental Results

A. Experimental Setup

The experiments were conducted in a 100-m^3 concrete pond for white-leg shrimp culture at the College of Aquaculture and Fisheries, Can Tho University. The shrimp were stocked at a density of 300 individuals per cubic meter, with an initial body weight of 3–4 g per individual. The aeration system was operated continuously to maintain stable environmental conditions throughout the 60-day experimental period. Fig. 11 shows the automated feeding system deployed under practical pond conditions, with the hydrophone positioned 18 cm above the feeding tray at the pond bottom to capture shrimp acoustic signals.

The procedure of one control cycle for the automated shrimp feeding operation is illustrated in Fig. 12. At the beginning of a feeding cycle, the Server instructs the Central controller to activate the Feeder motor to dispense feed for a predefined duration. After dispensing, the Central controller sends a notification to the Server; the Server then enables the acoustic signal processing mode and instructs the Central controller to start recording, after which the recorded data are transmitted back to the Server. At the Server, the acoustic data are stored and preprocessed through noise filtering and conversion into spectrogram images before being fed into the Faster R-CNN model for detection. After the deep learning model estimates the number of feeding shrimp, the result is passed to a decision algorithm to determine the duration of the next feed dispensing. The Server then sends a command to the Central controller to activate the Feeder motor according to the rules of the fuzzy logic algorithm described previously. This procedure is repeated until the number of feeding shrimp falls below a predefined threshold or the feeding process is terminated. The system is programmed to operate daily from 06:00 to 21:00. At 20-minute intervals, the acoustic evaluation module is automatically triggered to assess shrimp feeding activity, thereby enabling appropriate decisions on subsequent feed dispensing.

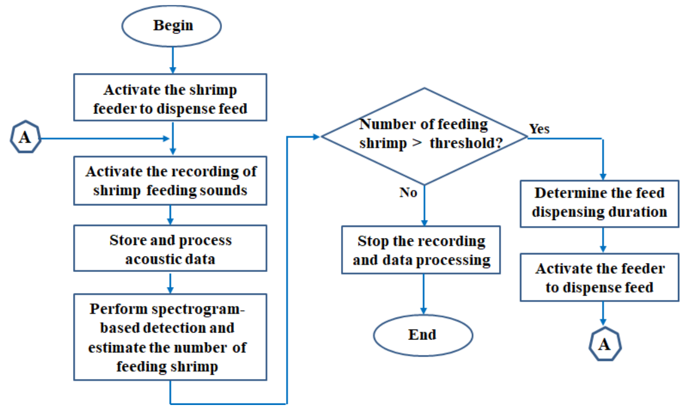


Fig. 12. Control flow of a feeding cycle.

B. Evaluation of the Effectiveness of the Automated Shrimp Feeding Method

In this study, a shrimp pond operated under the traditional manual feeding regime will serve as a reference to evaluate the effectiveness of the proposed automated shrimp feeding system. In this regime, shrimp were fed at fixed times five times per day, namely at 06:00, 11:00, 14:00, 17:00, and 20:00. The feed ration was determined based on the average body weight of the shrimp at each developmental stage, in accordance with standard pond management practices (SFP/Standard Feeding Protocol). The shrimp growth performance and feed consumption over the two-month experimental period are summarized in Table II.

Table II shows that the SFP feeding regime exhibited a consistent growth trend over time, with the average body weight increasing from 3.6 to 21.11 g per shrimp, while the number of individuals per kilogram decreased from 277.78 to 47.37 after 60 days. The average daily feed consumption peaked at 16.38 kg/day (Week 6) and slightly declined toward the end of the culture period (14.26 kg/day, Week 8), reflecting ration adjustments to minimize feed waste. The total feed input was 781.37 kg; harvested biomass reached 578.64 kg, corresponding to an estimated 27,420 shrimp, with a survival rate (SR) of approximately 91.4% and a feed conversion ratio (FCR) of 1.35. Overall, the SFP method resulted in stable growth, acceptable feed utilization efficiency, and a high survival rate.

Table III shows that under the automated feeding method, the average body weight increased from 3.60 g per shrimp (Day 1) to 23.64 g per shrimp (Day 60), reflecting a clear growth trend over the experimental period. Along with the increase in individual shrimp weight, the stocking density decreased from 277.78 shrimp/kg to 42.30 shrimp/kg, consistent with the growth pattern as body size increased over time. The average daily feed consumption rose from 4.64 kg/day in the initial stage to 14.19 kg/day in the final stage, with the total feed input for the entire culture cycle reaching 701.46 kg. The relatively stable daily feed consumption observed during the intermediate stages, despite the continued increase in shrimp weight, indicates the effectiveness of ration adjustment based on feeding behavior. At the end of the experiment, the harvested biomass reached 640.83 kg, with an SR of 90.36% and an FCR of 1.09.

The results indicate that the total feed input in the automated feeding method was 701.46 kg, which was 10.23% lower than that of the SFP approach (781.37 kg), while the FCR decreased from 1.35 to 1.09. The average daily growth (ADG) in the automated feeding treatment reached 0.33 g/shrimp/day, approximately 13.8% higher than that of the SFP treatment (0.29 g/shrimp/day). The survival rates in the two treatments were 90.36% (automated) and 91.39% (SFP), respectively, indicating only a minor practical difference. Through the designed web interface, farm managers can monitor variations in the intensity of shrimp feeding acoustic signals across feeding cycles, enabling real-time assessment of feeding activity. Monitoring fluctuations in the ration supplied to shrimp, together with comparisons of feed consumption among culture stages, allows the evaluation of feed utilization efficiency (Fig. 13). These results demonstrate that the proposed automated shrimp feeding system has strong potential to improve feed utilization efficiency.

TABLE. II. GROWTH PERFORMANCE AND FEED UTILIZATION UNDER THE STANDARD FEEDING PRACTICE (SFP)

Period (21/10/2025 to 19/12/2025)	**Growth** (*shrimp/kg*)	**Weight** (*g/shrimp*)	**Average daily feed consumption** (*kg/day*)	**Total feed consumption** (*kg*)
Week 1	277.78	3.6	6.75	47.25
Week 2	250.63	3.99	10.77	75.36
Week 3	178.89	5.59	11.74	82.18
Week 4	114.29	8.75	14.44	101.05
Week 5	82.92	12.06	16.28	113.96
Week 6	64.10	15.6	16.38	114.66
Week 7	55.34	18.07	15.73	110.11
Week 8	47.37	21.11	14.26	136.81
Total				**781.37**

**Notes: Week 8 has 11 days.*

TABLE. III. GROWTH PERFORMANCE AND FEED UTILIZATION UNDER THE ACOUSTIC-BASED FEEDING METHOD

Period (21/10/2025 to 19/12/2025)	**Growth** (*shrimp/kg*)	**Weight** (*g/shrimp*)	**Average daily feed consumption** (*kg/day*)	**Total feed consumption** (*kg*)
Week 1	277.78	3.6	4.64	32.48
Week 2	232.02	4.31	9.77	68.39
Week 3	162.60	6.15	11.21	78.47
Week 4	103.95	9.62	14.43	101.01
Week 5	74.02	13.51	12.15	85.05
Week 6	57.24	17.47	13.11	91.77
Week 7	47.66	20.98	12.60	88.20
Week 8*	42.30	23.64	14.19	156.09
Total				**701.46**

**Notes: Week 8 has 11 days.*

Fig. 13. Daily feed ration and monthly cumulative feed amount chart.

V. CONCLUSION AND FUTURE WORK

An automated feeding system driven by acoustic feedback from shrimp feeding activity was developed and experimentally validated. Feeding behavior was detected and analyzed in real time using spectrogram representations of "click" sounds and a Faster R-CNN–based framework, enabling feed delivery to be adjusted according to shrimp demand. A wavelet-based filtering method effectively suppressed background noise in practical pond environments. Field results confirmed improved performance compared with the traditional feeding practice (SFP), including a 10.23% reduction in feed consumption, a lower feed conversion ratio (1.09 versus 1.35), and higher average daily growth (0.33 versus 0.29 g/shrimp/day). The open-source Python–based implementation further enhances the practicality and scalability of acoustic-driven feeding in commercial aquaculture. Future work will extend validation across diverse farming conditions and integrate multimodal sensing and adaptive optimization to increase decision reliability and system robustness.

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DECLARATION ON GENERATIVE AI

The authors acknowledge using ChatGPT to improve the clarity and grammar of the manuscript. The content, analysis, and conclusions remain the sole responsibility of the authors.

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